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EXPLAINABLE ARTIFICIAL INTELLIGENCE MODEL FOR PREDICTIVE MAINTENANCE IN SMART AGRICULTURAL FACILITIES

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ABSTRACT

Artificial Intelligence (AI) applications in Smart Agricultural Facilities (SAF) often face challenges related to explainability, limiting farmers' ability to fully utilize their capabilities. This study addresses this gap by proposing a model that integrates eXplainable Artificial Intelligence (XAI) with Predictive Maintenance (PdM). The model aims to offer predictive insights and explanations across four key dimensions: data, model, outcome, and end-user. This approach represents a paradigm shift in agricultural AI, transforming how these technologies are interpreted and applied. The proposed model outperforms existing approaches, demonstrating notable improvements in performance. Specifically, the Long-Short-Term Memory (LSTM) classifier shows a 5.81% improvement in accuracy, while the eXtreme Gradient Boosting (XGBoost) classifier achieves a 7.09% higher F1 score, a 10.66% boost in accuracy, and a 4.29% increase in Receiver Operating Characteristic-Area Under the Curve (ROC-AUC). These results suggest that the model can enhance maintenance predictions in real-world agricultural settings. Additionally, this study offers valuable insights into data purity, both global and local explanations, and counterfactual scenarios in the context of PdM for SAF. By emphasizing explainability alongside traditional performance metrics, the study advances AI applications in agriculture. It also encourages future research in areas like multi-modal data integration and the implementation of Human-in-the-Loop (HITL) systems, which can improve AI effectiveness while addressing ethical considerations such as Fairness, Accountability, and Transparency (FAT) in agricultural AI.

I.INTRODUCTION

The integration of Artificial Intelligence (AI) in Smart Agricultural Facilities (SAF) has the potential to revolutionize the agriculture industry by optimizing operations, improving resource management, and enhancing productivity. Predictive Maintenance (PdM) is one of the most promising applications of AI in this context, as it enables the early detection of equipment failures, thereby reducing downtime and maintenance costs. However, despite its effectiveness, the adoption of AI-based PdM systems in agriculture is often hindered by a significant challenge: the lack of explainability. Farmers and operators, who may not possess deep technical knowledge, struggle to understand the decision-making processes of AI systems, making it difficult to trust and effectively utilize these technologies.

To address this challenge, the field of eXplainable Artificial Intelligence (XAI) has emerged as a crucial area of research, aiming to make AI models more transparent and interpretable. In the context of predictive maintenance, explainability is particularly important, as it helps users understand why certain

maintenance actions are recommended, allowing them to make informed decisions. This study introduces an explainable AI model specifically designed for PdM in Smart Agricultural Facilities, which integrates both predictive insights and explanations. The model provides clarity across four key dimensions: data, model, outcome, and end-user, ensuring that stakeholders can comprehend the rationale behind AI-driven predictions.

By combining explainability with predictive maintenance, this model aims to enhance user trust and engagement, bridging the gap between complex AI algorithms and the practical needs of farmers. In addition to improving the interpretability of AI models, the study demonstrates how this model improves predictive performance, offering measurable improvements in accuracy, F1 score, and other evaluation metrics. Furthermore, the research highlights the importance of incorporating ethical considerations, such as Fairness, Accountability, and Transparency (FAT), into the deployment of AI in agriculture.

The remainder of this paper discusses the design and implementation of the explainable AI model, evaluates its performance in comparison to existing approaches, and outlines future directions for integrating multi-modal data and Human-in-the-Loop (HITL) systems to further enhance AI-based predictive maintenance in Smart Agricultural Facilities. Through this work, we aim to advance the application of AI in agriculture, ensuring that AI technologies are not only effective but also accessible and trustworthy for farmers.

II.LITERATURE REVIEW

This study conducted an extensive literature review to critically examine advanced AI-driven Predictive Maintenance (PdM) techniques, with a specific focus on eXplainable Artificial Intelligence (XAI) models. The goal was to assess the potential of XAI in enhancing maintenance practices by providing clearer insights into model decisions. The review aimed to highlight the strengths, limitations, and practical applicability of various XAI approaches in PdM, providing a comprehensive overview of the current state and future directions for integrating XAI in agricultural PdM systems.

A. Predictive Maintenance Approaches

The review identified three key PdM approaches: (1) anomaly detection, (2) prognostics, and (3) diagnostics [21]. Anomaly detection focuses on identifying unusual patterns in data, while prognostics predict future system performance. Diagnostics, on the other hand, aim to identify current issues based on performance analysis. Among the studies reviewed, eleven studies concentrated on prognostics [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], three focused on anomaly detection [41], [42], [43], and two combined both prognostics and diagnostics [40], [44].

Notably, none of the studies exclusively concentrated on diagnostics, highlighting a significant gap in the existing literature. Future research should explore how combining anomaly detection and prognostics can lead to more effective diagnostic capabilities, improving the overall robustness and efficiency of PdM systems in Smart Agricultural Facilities (SAF).

B. Deep Learning and Machine Learning in Predictive Maintenance

For prognostics, techniques such as Recurrent Neural Networks (RNNs) and Long-Short-Term Memory (LSTM) networks emerged as highly effective, achieving an impressive 90.07% accuracy [33]. In predicting Remaining Useful Life (RUL), more advanced models like Bidirectional Recurrent Neural Networks (Bi-RNNs) and LSTMs pushed the boundaries, reaching 96.15% accuracy [30]. LSTMs, in particular, have shown promise in anomaly detection tasks, often in combination with One-Class Support Vector Machines (OC-SVM), which help significantly reduce false alarms [38]. However, OC-SVMs struggle with supervised problems and may not always be applicable in all scenarios.

Another study that applied Random Forest (RF) in prognostics incorporated AutoML, demonstrating versatility, particularly in component-level analysis [32], [36]. However, while AutoML has democratized machine learning by automating model selection, its generalist approach limits the ability to optimize specific models for particular tasks [45]. Ensemble Learning (EL) techniques also proved valuable in the prognostics domain, particularly within manufacturing industries [36]. Despite the complexity of other approaches like Balanced K-Star, Multi-Layer Perceptron (MLP), Extreme Learning Machine (ELM), and Transfer Learning (TL), they provide viable alternatives for PdM. Additionally, Deep Convolutional Autoencoders were explored in some studies for their potential in predictive maintenance [34], [35], [40], [46]. While diagnostics in PdM remains underexplored, the few studies that have touched on it suggest that further attention is needed in this area [40].

C. Explainable Artificial Intelligence

In the rapidly evolving fields of deep learning (DL) and machine learning (ML), sophisticated models have become increasingly prevalent across industries such as healthcare, finance, and agriculture. However, the complexity of these models often obscures their decision-making processes, raising significant concerns about their transparency and interpretability [23]. This lack of clarity has driven the need for explainable AI (XAI), a concept that goes beyond simple transparency to make the decision-making of DL and ML models understandable to both experts and non-experts alike. Explainability involves breaking down the inner workings of these models, helping users comprehend how decisions are made and fostering trust in AI systems. This need for explainability encompasses multiple facets, each of which plays a crucial role in enhancing the reliability and understanding of DL models.

1) Dimensions of Explainability

A review of the literature identified four primary dimensions of explainability: (1) data, (2) model, (3) outcome, and (4) end-

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user. The data dimension focuses on the limitations and potential of the data used in AI models [22]. Despite its importance, many studies failed to assess whether the data was sufficient to support the insights sought, highlighting the need for further research into the data capabilities in predictive maintenance for Smart Agricultural Facilities (SAF). The model dimension investigates how input data influences model predictions [22]. Often, assumptions of feature independence are made, which can introduce bias. While most studies addressed the model dimension, a few also considered both the model and outcome dimensions [30], [31], [32], [36], [39]. However, only two studies specifically focused on outcome explainability [34], [37], pointing to a research gap in understanding the reasoning behind individual predictions made by AI models. Addressing this gap could enhance both transparency and decision-making in AI systems. The end-user dimension, which tailors explanations to non-technical users [47], was largely overlooked in the literature, highlighting the need for research that makes AI systems more accessible to a broader audience.

2) Approaches to Explainability

From the reviewed studies, six primary approaches to explainability emerged: (1) local explainability, (2) global explainability, (3) model-specific, (4) model-agnostic, (5) model-centric, and (6) data-centric approaches. Local explainability provides clarity on individual predictions, while global explainability aims to reveal the overall behavior of the model. Although two studies explored both local and global explainability [33], [41], none focused exclusively on global explainability, indicating a significant research gap. Thirteen studies delved into local explainability alone [30], [31], [32], [34], [35], [36], [37], [38], [39], [40], [42], [43], [44].

Model-specific approaches are tailored to particular AI models, whereas model-agnostic methods are applicable across different types of models. Ten studies used model-agnostic approaches [30], [31], [32], [34], [36], [38], [40], [42], [43], [44], while three focused on model-specific techniques [33], [35], [37]. Only two studies combined both approaches [39], [41]. Model-centric approaches analyze the relationships between inputs and outputs within models, while data-centric approaches emphasize the quality and relevance of the data [47]. All studies in the review employed model-centric approaches, while data-centric strategies were rarely explored, indicating an important area for further research.

D. Explainable Artificial Intelligence for Predictive Maintenance

Several XAI techniques have been applied to predictive maintenance, with SHapley Additive exPlanations (SHAP) standing out for its ability to clarify the impact of features on predictions, particularly in reducing false alarms [38], and improving diagnostic interpretation [40], [44]. Despite its usefulness, SHAP's complexity can be a barrier to its broader application. Similarly, Local Interpretable Model-agnostic Explanations (LIME) has been used to provide localized explanations for predictions, particularly in anomaly detection for transportation systems [41]. While LIME excels at explaining individual predictions, its focus on local explanations limits its utility for providing a

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comprehensive understanding of the entire model.

Layer-wise Relevance Propagation (LRP), typically used in deep learning models, offers detailed insights into prediction influences [33]. While LRP has demonstrated effectiveness in its applications, it is highly model-specific. A comparison of LIME, SHAP, and Explain Like I Am Five (ELI5) revealed differences in the efficiency and feature attribution of each method [39]. LIME was found to be efficient, while ELI5 provided more intuitive explanations, though it lacked the versatility to work across different models. Counterfactual Explanations (CFE), which focus on generating "what-if" scenarios, have gained popularity for making AI systems more acceptable, especially for non-experts [34], [36].

III.SYSTEM ARCHITECTURE

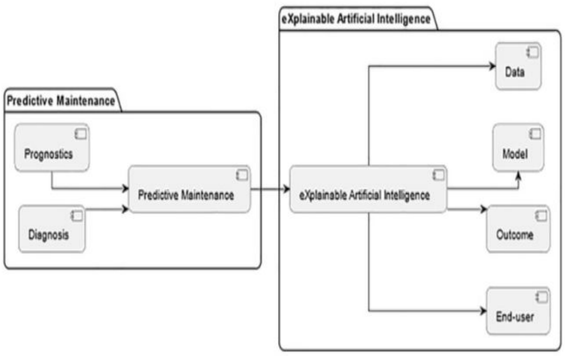

Fig1.System Architecture

The system architecture for the proposed Explainable Artificial Intelligence (XAI) model for Predictive Maintenance (PdM) in Smart Agricultural Facilities (SAF) is structured to ensure efficient data flow, reliable predictive capabilities, and transparent insights for stakeholders. This architecture consists of several layers that integrate AI, data processing, and user interaction, each contributing to the overall functionality and transparency of the system.

IV.METHODOLOGY

Data Collection Layer

The Data Collection Layer is responsible for gathering real-time data from various sources within the agricultural facility. This includes data from Internet of Things (IoT) sensors, such as temperature, humidity, soil moisture, and machinery health sensors. These sensors continuously monitor critical parameters within the facility, providing essential data for predictive maintenance tasks. The data is processed by edge devices before being transmitted to the cloud, reducing latency and ensuring that only relevant data is sent for further analysis. Additionally, external data sources, such as weather forecasts and historical maintenance records, are integrated into the system to enrich the predictions.

Data Preprocessing Layer

Once the data is collected, it enters the Data Preprocessing Layer, where it undergoes cleaning, normalization, and feature extraction. Raw data often contains noise, missing values, or inconsistencies that can affect the performance of predictive models. This layer handles these issues by filling in missing values, standardizing data units, and extracting useful features, such as identifying patterns that indicate machine wear or potential failures. These preprocessed data are then formatted for analysis by machine learning models, ensuring high-quality input that facilitates accurate predictions.

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Predictive Maintenance Model Layer

The core of the system lies in the Predictive Maintenance Model Layer, where machine learning and deep learning algorithms are applied to predict potential failures and schedule maintenance. This layer utilizes advanced models like Long-Short-Term Memory (LSTM) networks for time-series analysis of sensor data and eXtreme Gradient Boosting (XGBoost) for feature-based predictions. The system forecasts the Remaining Useful Life (RUL) of machinery, predicts failures, and provides recommendations for maintenance activities. Anomaly detection algorithms within this layer help to flag unusual patterns, which can indicate early signs of failure or inefficiencies.

Explainability Layer

The Explainability Layer ensures that the predictive maintenance models are transparent and understandable to end-users. By applying techniques like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and Counterfactual Explanations (CFE), this layer provides clear insights into how the model arrived at its predictions. For instance, SHAP explains which features, such as environmental conditions or machinery performance metrics, most influenced the prediction of a potential failure. LIME helps in understanding individual predictions, while CFE offers "what-if" scenarios that help users explore alternative outcomes. This layer ensures that both technical and non-technical users can understand and trust the predictions made by the AI system.

Decision Support Layer

The Decision Support Layer serves as the interface through which end-users interact with the system. Based on the AI predictions and their explanations, this layer provides actionable insights, such as maintenance alerts and recommendations. For example, users may receive notifications about upcoming maintenance needs based on predictive models, along with the reasoning behind these alerts. The system also provides detailed maintenance recommendations, including the necessary actions and optimal timing, to reduce the risk of failure. Additionally, the layer includes a feedback loop, where users can provide insights to improve the model's accuracy over time.

User Interface Layer

The User Interface (UI) Layer provides an intuitive and user-friendly interface for interacting with the predictive maintenance system. The UI includes dashboards that display real-time sensor data, predictive insights, and maintenance recommendations in a visually clear format. These dashboards also provide interactive tools for users to explore model predictions, view feature importance, and access explanations of individual predictions. The system is designed to be accessible across different devices, including desktops, tablets, and mobile devices, ensuring that stakeholders can access critical information anywhere in the facility.

V.CONCLUSION

The Explainable Artificial Intelligence (XAI) model for Predictive Maintenance (PdM) in Smart Agricultural Facilities (SAF) presents

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a robust and innovative solution to address the growing challenges faced by modern agricultural operations. By combining advanced machine learning algorithms with explainability techniques, this system not only predicts potential failures and maintenance needs with high accuracy but also ensures transparency and trust in AI-driven decisions. The integration of technologies like Long-Short-Term Memory (LSTM) networks and eXtreme Gradient Boosting (XGBoost) offers precise predictions of Remaining Useful Life (RUL) and anomaly detection, while explainability methods such as SHAP, LIME, and Counterfactual Explanations (CFE) make the system's decisions accessible and understandable to non-expert users.

The system's architecture, designed to handle real-time data collection, preprocessing, and predictive modeling, enables seamless integration into agricultural facilities, enhancing operational efficiency and minimizing downtime. Moreover, the Cloud/Edge Computing model ensures scalability and low-latency processing, providing timely predictions and maintenance alerts. The User Interface Layer makes it easier for stakeholders to interact with the system and act on AI-driven insights, improving overall decision-making.

Ultimately, this project contributes significantly to the field of agricultural AI by demonstrating the importance of explainability in AI systems. It promotes more effective, data-driven maintenance practices in SAF, offering a pathway to more sustainable, cost-efficient, and transparent agricultural operations. Future research can explore expanding the system's capabilities through multi-modal data integration, further refinement of explainability methods, and incorporating Human-in-the-Loop (HITL) systems to enhance the decision-making process. By addressing key concerns such as Fairness, Accountability, and Transparency (FAT), this approach sets a new standard for AI applications in the agricultural industry.

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